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Fuzzy Distributed Genetic Approaches for Image Segmentation

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This paper presents a new image segmentation algorithm (called FDGA-Seg) based on a combination of fuzzy logic, multiagent systems and genetic algorithms. We propose to use a fuzzy representation of the image site labels by introducing some imprecision in the gray tones values. The distributivity of FDGA-Seg comes from the fact that it is designed around a MultiAgent System (MAS) working with two different architectures based on the master-slave and island models. A rich set of experimental segmentation results given by FDGA-Seg is discussed and compared to the ICM results in the last section.

Keywords: image segmentation, fuzzy logic, Markov random field, multiagent systems, genetic algorithms, chaotic system

1. Introduction

Image segmentation is a critical step of any image analysis application, it has a significant influence on the quality of subsequent treatments as it isolates and extracts the pertinent features needed by image analysis processes. It consists of partitioning the image into a set of disjoint regions [15]. The union of such regions gives the whole original image. Image segmentation is a wide-ranging domain with a rich literature describing unnumbered set of methods.

Image segmentation based on the Markov Random Field (MRF) is among the pioneers and very reliable approaches. It has been subject to a large list of publications since three decades [13, 2, 9, 10, 17]. The Besag's Iterated Conditional Modes (ICM) [2] and the Simulated Annealing (SA) [13, 19] are two particularly interesting MRF-based segmentation methods. Starting with a sub-optimal configuration, the ICM maximizes the probability of the segmentation field by deterministically and iteratively changing pixel classifications. The ICM is computationally efficient [10], but its convergence depends strongly on the initialization. Theoretically, SA always converges to the global optimum [13]. However, SA remains a computationally intensive method compared to ICM [10]. Other approaches based on single-population Genetic Algorithms (GAs) [14, 16, 1, 3, 5, 22] require heavy use of memory and a very important convergence time. However, the process of GA design is significantly faster than in the case of single population. Also, evolutionary algorithms have a natural mapping onto parallel architectures. In various domains of applications, fuzzy logic [36] techniques (e.g. fuzzy operators, fuzzy measures, fuzzy criteria, etc.) have been used to model GA components in order to improve the GA behavior. Please refer to these two excellent surveys [24, 8] for a bibliographical synthesis of hybrid methods and their applications.

In this paper, we combine GAs and fuzzy logic within a MultiAgent-based framework to define a new image segmentation approach. Through the remaining part of this paper, we refer to this algorithm by FDGA-Seg for Fuzzy Distributed Genetic Algorithm Segmentation. The distributivity aspect comes from the fact that FDGA-Seg is designed around a MultiAgent System (MAS). The FDGA-Seg is designed to work with two different MAS architectures (or models) based on the master-slave and island models (Section 2.2 gives more details about these two models). A MAS is a system composed of several software agents, collectively capable of reaching goals that are difficult to achieve by an individual agent or monolithic system. More details about MASs can be found in references [32, 33, 11, 31].

The organization of this paper is as follows. Section 2 presents image and MRF related concepts. It also presents the master-slave and the island models which support the implementation of MAS and the GA. Section 3 is the bulk of this paper, it details the proposed FDGA-Seg algorithm by describing the fuzzy representation, the genetic operators and the MAS distributed architecture. Some experimental results are discussed in Section 4. The conclusion and some ideas for future extensions of this work are given in Section 5.

2. Related Concepts

2.1. Image and MRF

Let $S = \{1,..,t,..,MN\}$ be an image which specifies the gray levels for $MN = M \times N$ pixels, where M and N are the number of rows and columns of the image, t is called a site. Given an initial image X, referenced so far as "the true image", and another image Y obtained by adding Gaussian noise process to the true image, Y is referenced so far as "the observed image". Both images are represented by the MN random vectors:
$X = (X_1,\ldots,X_t,\ldots,X_{MN})$, $X_t \in \{1,\ldots,C\}$,
$Y = (Y_1,\ldots,Y_t,\ldots,Y_{MN})$, $Y_t \in \{0,\ldots,255\}$,
where C is the number of cluster or classes in the image [10].

The MRF is a discrete stochastic process whose global properties are controlled by means of local properties. The Ising model highlight MRF and facilitate their use in different domains of application [20]. In fact, the Ising model is the best known and the most used in MRF image segmentation.

In 1924 Ernest Ising tried to use a model, called thereafter 'Ising model', in order to explain certain empirically observed facts about ferromagnetic materials.

The Ising model considers a sequence $(0,\ldots,i,\ldots,a)$ of sites on the line. At each site, there is small dipole or spine which at any given time is in up position or in down position. A configuration $x = (x_0,\ldots,x_i,\ldots,x_a)$ is considered as a MRF where $x_i = +$ if the site i is in a spin up position and $x_i = -$ if the site i is in a spin down position. Ising defined a probability measure on the all possible configurations and assigned an energy function which is caused by neighboring spins interactions and the external magnetic field property. The Ising model is applicable on two dimension lattice (image).

The Ising model can provide a simple illustration of a collection of MRFs. Thus, it has been most investigated and used in MRF. In this paper, we assume the notation introduced in the paper and we talk about an isotropic second-order Ising-MRF model. A neighborhood system $NS = (N_i \subset S, i \in S)$ is a subset collection N_i of S verifying: (1) $i \notin N_i$ and (2) $j \in N_i \Leftrightarrow i \in N_j$. A clique c is a set of points which are all neighbors to each other: $\forall r \in c$ and $t \in c$ then $r \in N_t$.

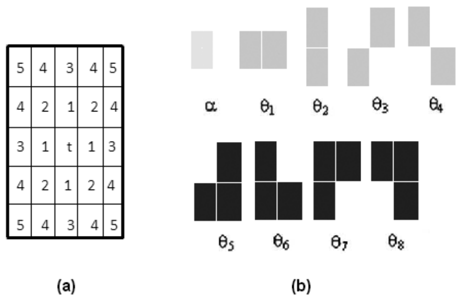

Figure 1. (a) A neighborhood system, (b) Cliques of the second order neighborhoods.

The structure of the neighborhood system (see Figure 1.(a)) determines the MRF order. For a first order, the neighborhood of a site consists of its four nearest neighbors. In a second order, the neighborhood of a site consists of the eight nearest neighbors. The clique structures for a second order MRF are illustrated in Figure 1.(b).

Let $X = (X_1,\ldots,X_{MN}) \in \Omega$, where Ω is the set of all possible configurations of the segmented images. X is a MRF with respect to NS if:

1. $\forall x \in \Omega : P(X = x) > 0$
2. $\forall t \in S \quad x \in \Omega : P(x_i/x_j, j \in S - \{i\})$
   $= P(x_i/x_j, j \in N_i)$

X is a MRF on S with respect to NS if and only if $P(X = x)$ is a Gibbs distribution defined by the a-priori probability $P(X = x) = e^{-U(x)}/Z$ where $Z = \sum_{x\in\Omega} e^{-U(x)}$ is the partition function and $U(x)$ is the energy function:

$$U(x) = \sum_{t=1}^{MN} \sum_{r\in N_t} \theta_r \delta(x_t, x_r) \qquad (1)$$

where θ_r are the clique parameters, $\delta(a,b) = -1$ if $a = b$ and $\delta(a,b) = 1$ if $a \neq b$. $P(X = x)$, called the a-priori probability follows the Gibbs distribution.

We assume an isotropic second-order Ising model, so in equation 1, $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \beta$. This model uses only cliques that contain no more than 2 sites having non-zero potentials. In this paper, a second order model is used, so the number of clique types is 4 presented in gray (see Figure 1.(b)). The a-posteriori probability $P(x/y)$ is a Gibbs distribution given by: $P(x/y) = e^{-U(x/y)}/Z_y$ where Z_y is the normalization constant and $U(x/y)$ is the energy function [17] given in equation 2:

$$U(x/y) = \sum_{t=1}^{MN} [\ln(\sqrt{2\Pi}\sigma_{xt}) + \frac{(y_t - \mu_{xt})^2}{2\sigma_{xt}^2} + \sum_{r\in N_t} (\beta\delta(x_t, x_r))] \qquad (2)$$

where β is a positive model parameter that controls the homogeneity of the image regions.

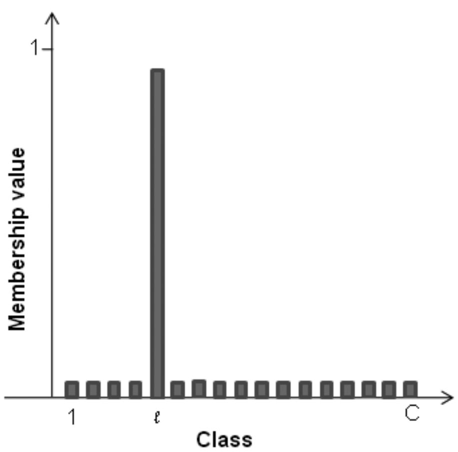

Figure 2. Membership functions for a site-label with best label ℓ.

Let $X = \{x_1, x_2, \ldots, x_{MN}\}$ be an image with a set of classes $\{1, 2, \ldots, C\}$, and x_j be the gray level of the j^{th} site in X. Let $\mu(X)$ be the fuzzy membership degrees derived from X given by $\mu(X)=\mu(x_1), \mu(x_2), \ldots, \mu(x_{MN})$.

$\mu(.)$ is obtained by operating a fuzzifier on X. This fuzzifier performs a mapping from crisp data values X into a fuzzy set represented by $\mu(X)$. We denote by $\mu_i(x_j)$ the fuzzy membership degree of site label x_j to fuzzy subset class i of X (see Fig. 2).

2.2. MAS Architectures

In this subsection, we briefly introduce the master-slave and island models which are used to implement the GA and support FDGA-Seg.

In the master-slave model, the MAS is composed of a set of segmentation agents (slaves) connected to a coordinator agent (master). During the initialization phase, each agent creates a fuzzy set of images from the observed image using $K-$means and a chaotic membership function. The behavior of each agent depends on its own initial data. During the evolution cycle, each agent performs ICM on its own crisp initial image, and then transmits its initial and segmented images together with the fitness value to the coordinator agent which selects and saves the best segmentation, performs genetic operators, then retransmits the new crisp initial images to all the segmentation agents for another segmentation cycle.

Island models are a popular and efficient way to implement GAs and improve their behaviors [6, 34, 25]. In this model, the population of the GA is clustered into a set of subpopulations called demes (or islands). The various islands maintain some degree of independence. They explore deferent search spaces, but share information by means of the migration operators [39, 38]. Recently, a fuzzy adaptive search method for island parallel genetic algorithms is proposed in [28]. They proposed a method that is able to tune the genetic parameters according to the search stage by the fuzzy reasoning. In FDGA-Seg, we propose to combine fuzzy logic concepts with an island-based MAS model. This combination results in a segmentation mechanism composed of a set of agents called island agents [37].

3. FDGA-Seg the Proposed Segmentation Algorithm

There is potential risk that the distributed evolutionary approach can be attracted to a local minimum, especially when small size subpopulations and not appropriate initial parents are used [25]. Such local attraction can be avoided using a new fuzzy initialization based on the chaotic system. We propose to use the extreme sensitivity of chaos to define a fuzzy set which produces a potentially good starting values in the initialization of the FDGA-Seg. The intrinsic features of the chaotic system allows to use chaos as a good random number generator [27, 26].

The simplest non linear mappings is called logistic map, it exhibits order-to-chaos transitions. This one-dimension logistical map is given in equation 3:

$$z_{k+1} = f(\mu, z_k) = \mu z_k(1 - z_k), \quad z_k \in [0, 1] \tag{3}$$

where $z_{k,k=0,1,...}$ is the value of variable z at the k^{th} iteration, z_k represents the extinction rate where 0 represents extinction and 1 the maximum viable population. The bifurcation parameter μ represents the growth rate of the population.

In equation 3, the variable z_k represents the extinction rate where 0 represents extinction and 1 the maximum viable population. The bifurcation parameter μ represents the growth rate of the population. According to equation 3, we assume that the higher the scale of the growth rate, the higher the value the population would take.

The second chaotic system is derived from chaotic neuron [29, 35] and produced by a new chaotic map defined by:

$$z_{k+1} = \eta z_k - 2tanh(\gamma z_k)exp(-3z_k^3), \eta \in [0, 1] \tag{4}$$

where $z_{k,k=0,1,...}$ represents the internal state of the neuron, η is a damping factor of nerve membrane and the second term of the equation 4 given by $f(z_k) = 2tanh(\gamma z_k)exp(-3z_k^3)$ is a non-linear feedback. So, we use this chaotic mapping to define a fuzzy suboptimal image according to a chaotic mapping.

Let $x^0 = (x_1^0, \ldots, x_s^0, \ldots, x_{MN}^0)$ be a crisp initial image created using $K-$means. This initial image will undergo chaotic perturbation by applying formula 5 as follows: for a given site s selected with a truth degree of 0.005, the site label $x_s^0 \in \{1, .., C\}$ will possibly take the following new value:

$$x_s^0 = \alpha \lfloor C * z_{k_s} \rfloor + (1 - \alpha) \lfloor C * w_{k_s} \rfloor \tag{5}$$

For a given z_0, the chaotic variables $z_{k_s}, s = 1, 2, \ldots, MN$ are generated by the logistic map of equation 3 and for a given w_0, the chaotic variables $w_{k_s}, s = 1, 2, \ldots, MN$ are generated by the chaotic map of equation 4, where $k_i \in \{1, \ldots, 400\}$ is a randomly generated integer and α is a parameter in the interval $[0, 1]$.

In a classical definition of a crisp set, an element may or may not belong to a set. If the idea of partial truth is introduced, this concept may be extended to fuzzy sets. Thus, in fuzzy logic, an element may be a member of a set to a certain extent depending on the membership function which characterizes the set. We can use this concept in the image representation to find a robust justification argument.

For example, in classical sets [30], if we want to classify pixels by their gray values into three classes: dark, gray and white we define these sets as:

$f(x) =$ dark if $0 \leq x \leq 60$, gray if $60 \leq x \leq 200$, and white if $200 \leq x \leq 255$

But a pixel with gray value 62 is too dark to be classified as a gray pixel. If by incorporating fuzziness, we can rewrite the membership functions as shown in Figure 3. So, there is an ambiguity to classify the pixel with gray value 62 especially between dark and gray.

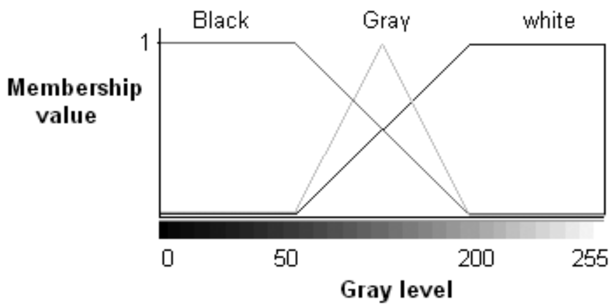

Figure 3. Membership functions for dark, gray and white colors.

This example shows that the pixels clustering cannot be resolved using classical approaches. In fact, a pixel is considered as a crisp element. It is obtained from the intensity of light of a scene collected by one or more sensors. A pixel may be considered as a quantity of matter modelled with some loss of information due to dimension reduction.

In this paper, we propose a fuzzy model in order to mimic how to distribute the information by a fuzzy classification of an imprecise suboptimal image. In fact, we suppose that gray tone images possess ambiguity within each pixel. So, regions of the initial image may be considered as fuzzy set. Therefore, the slightly perturbed images diversify the agents' initial data, which allows to reach different solutions in the configuration space.

This fuzzy representation gives a large diversification to our distributed approach. This uncertainty in the initialization information allows each agent to access to good solutions at a lower cost.

3.1. Fuzzy Image Representation

We can represent initial images by the fuzzy set:

$$x^0(\mu_s) = \begin{cases} \ell_{x_s} & \text{if } \mu_s > 0.005, \\ \alpha \lfloor C * z_{k_s} \rfloor + (1-\alpha) \lfloor C * w_{k_s} \rfloor & \text{else.} \end{cases}$$

with $s \in \{1, .., MN\}$, and ℓ_{x_s} is the best label found for x_s by the $K-$means rule and μ_s is a uniform random number in $[0, 1]$.

Let x^0 be the sub-optimal image created using $K-$means where $x_s^0 = \ell_{x_s}$. In this approach, we relax from $\{0, 1\}$ to the interval $[0, 1]$ concerning the assignment $K-$means rule of $x_s^0 = \ell_{x_s}$.

The justification of this hypothesis is that after dimension reduction of the space of real image, there is a loss of information in the new image representation. Defined by a fuzzy set, the fuzzy input image produces a variety of initial images for the segmentation agents to start with (see Figure 4). Also, our applied distributed GA is naturally familiarized with the fuzziness approach. Indeed, genetic operator is a Darwinian-based principle of reproduction which is 'the survival of the fittest'. We can interpret this concept as a fuzziness process.

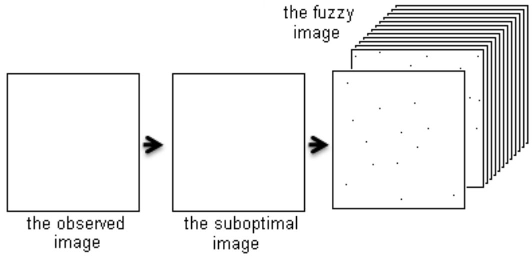

Figure 4. The fuzzy initialization of FDGA-Seg.

3.2. The Genetic Operators

3.2.1. The Population or Fuzzy Set

Our population can be obtained from a number of defuzzifications of a fuzzy initial image. So, each individual is a crisp initial image and its gene is defined by a site label belonging to $\{1, 2, \ldots, C\}$, which is the *alphabet*. Each chromosome is evaluated with a *fitness* measure via the energy function given in equation 2.

3.2.2. The Crossover

The crossover exchanges, with a probability of 0.9, genetic data between two parent chromosomes to produce offsprings. The parent chromosomes correspond to two crisp initial images for producing offsprings. For each mating, the crossover positions (line and column indexes) are selected randomly (see Figure 5).

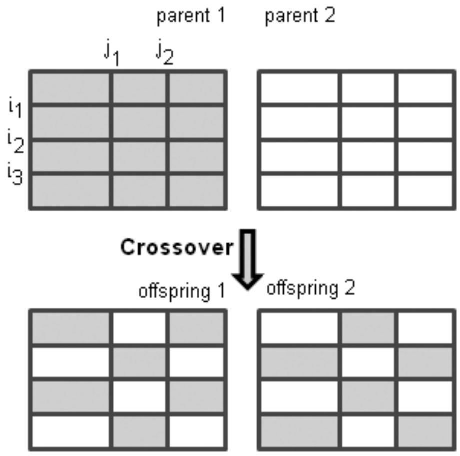

Figure 5. The two parents represent the initial images and the two offsprings are the new initial images. i_1, i_2, i_3 and j_1, j_2 are indexes of the cross line points and the cross column points.

3.2.3. The Mutation

The mutation is a rare, but extremely important event in GA. When a site label is mutated, it is randomly selected with a probability of 0.005 and replaced with another category from the alphabet. Each individual is considered as a crisp element that can be obtained by a mutation which is considered as defuzzification. The mutation phenomena open the door to fuzziness interpretation of such evolutionary approaches.

3.3. The Master-slave Model

We consider k segmentation agents (slaves) connected to a coordinator agent (master) as presented in Figure 6. This FDGA-Seg is an intensive way to find a very good or the best segmentation by genetically breeding of a population of initial images over a series of new generations of input images. The master-slave architecture of FDGA-Seg is detailed in Algorithm 1.

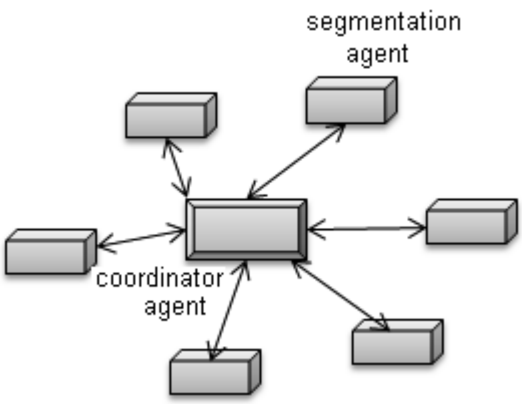

Figure 6. Communication network of the FDGA-Seg.

Algorithm 1. Step of FDGA-Seg based on master-slave MAS model.

1. In the initialization phase, each segmentation agent
   - performs $K-$means on the observed image,
   - applies a fuzzification on the $K-$means output image in order to define the fuzzy initial image.
   - applies a defuzzification to obtain a crisp initial image.
2. In the evolution cycle,
   - each segmentation agent: performs ICM starting from its own crisp initial image and then sends it with its segmented image and its fitness segmentation value to the coordinator agent.
   - The coordinator agent:
     — receives the messages from the agents,
     — saves the best segmentation and its fitness in the variables Best-Segmentation and U^* respectively.
     — performs the crossover and the mutation and retransmits the new offsprings to the segmentation agents.
3. The process repeats steps 2 and 3 until a stability of the system is reached.

3.4. The Island MAS Model

In this model, the population is considered as a fuzzy set and demes as fuzzy sub sets. This distributed model can be readily implemented in parallel computers, in which case, the advantages of the fuzzy representation are added to the parallel architecture to drastically reduce the evaluation number and execution time, and enhance the functioning of the FDGA-Seg. Indeed, the fuzzy set definition and the fuzzy logic can be considered like new strategy that offers a large diversification of starting data which gives some freedom in the solution searching activity.

Algorithm 2. The description of the island-MAS.

1. In the initialization phase, each island-agent
   - performs $K-$means on the observed image,
   - applies a fuzzification on the $K-$means output image in order to define the fuzzy initial image.
   - applies a defuzzification to compute a crisp initial image.
   - performs ICM starting from its own crisp initial image,
   - transmits this initial image, to the other island-agents to define the initial deme.
2. In the evolution cycle, each island-agent:
   - receives individuals from the different island-agents,
   - performs a GA on a deme: applies a crossover on peers of parents and performs a mutation on one or several individuals,
   - performs ICM starting from a good offspring,

- updates the best segmented image with its fitness,
- transmits the new good crisp initial image to the different island-agents for another segmentation process.

During initialization 4, each island agent performs a defuzzification in order to obtain a possible individual corresponding to a crisp initial sub-optimal image from the fuzzy initial image. Thanks to this migration strategy, the island agents exchange the judged good individuals selected among the offsprings (see Algorithm 2). Each island agent will contain a deme represented by the current good individuals. In the island strategy presented with a fully-connected model (see Figure 7), within each deme, a standard sequential GA is executed on a set of crisp initial images. However, each island agent performs GA on a deme in order to choose a new better crisp initial image. In fact, the island-MAS shares genetic material between crisp initial images in order to produce good initializations.

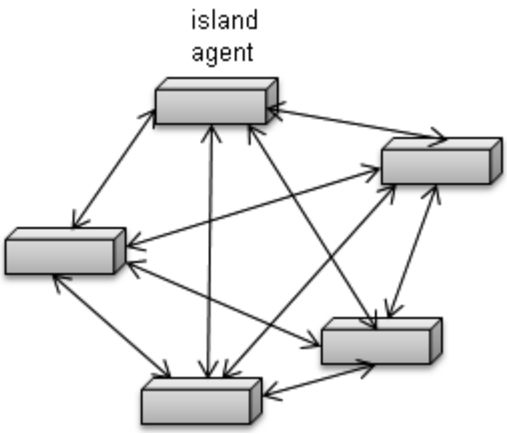

Figure 7. Communication network of the island-MAS.

At each cycle, each island agent receives the judged best individuals from the other Island agents, performs the GA on the current deme, runs ICM starting from a good enough offspring, updates the best segmented image and then retransmits this new initial image to the other island agents.

4. Experimental Results

We present the experimental results of the application of the proposed FDGA-Seg on synthetic as well as real data. Results are also compared to those produced by the ICM. We have used one value of β which is kept constant through each segmentation. The segmentation is evaluated by both visual examination and energy function. The observed y is the same starting discrete data for all algorithms. These experiments are performed by using Builder C++ 6 on a Pentium 4, CPU 2.66 GHz with 256 MB.

In Figure 8, we show a noisy flower image. It can be seen that different parts in the flower image are better segmented by FDGA-Seg (subfigures c and d) than by ICM (subfigure a), this is despite the interference and the thinness of some regions. Table 1 shows minimal values of the the energy for the examples of Figures 8-12. Also, in the blurred experience of the word "FUZZY" (see Figure 9), the FDGA-Seg extracts the characters better than ICM in spite of the attenuation of this Gaussian blur of the image.

Experiment	Approach	$U(x^*/y)/MN$
Figure 8.(b)	ICM	-4.0381
Figure 8.(c)	FDGA-Seg master-slave	-4.9851
Figure 8.(d)	FDGA-Seg Island-MAS	-4.9674
Figure 9.(b)	ICM	-5.1557
Figure 9.(c)	FDGA-Seg master-slave	-5.9341
Figure 9.(d)	FDGA-Seg Island-MAS	-5.9158
Figure 10.(b)	ICM	-3.3462
Figure 10.(c)	FDGA-Seg master-slave	-4.5398
Figure 10.(d)	FDGA-Seg island	-4.5727
Figure 11.(b)	ICM master-slave	-3.8780
Figure 11.(c)	FDGA-Seg master-slave	-4.6350
Figure 11.(d)	ICM Island-MAS	-4.8273
Figure 12.(b)	ICM master-slave	-4.1067
Figure 12.(c)	FDGA-Seg master-slave	-4.9623
Figure 12.(d)	ICM Island-MAS	-4.9425

Table 1. Minimal values of energy functions and parameters of the FDGA-Seg.

In Figure 10(a), the cast shadow of a manufactured object has a geometric shape. The two-class segmentation (see Figure 10) shows again a better robustness of the FDGA-Seg models against the speckle noise.

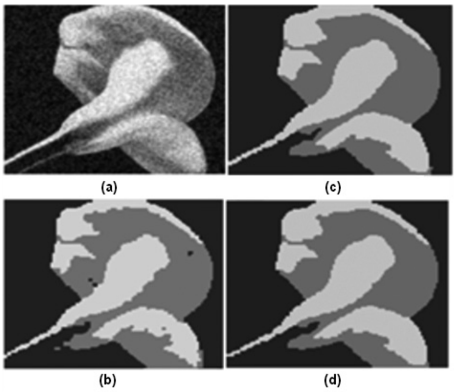

Figure 8. Segmentation of a noisy real scene. FDGA-Seg Iterations=50. (a) a flower, (b) ICM result, (c) FDGA-Seg master-slave result, (d) FDGA-Seg Island result.

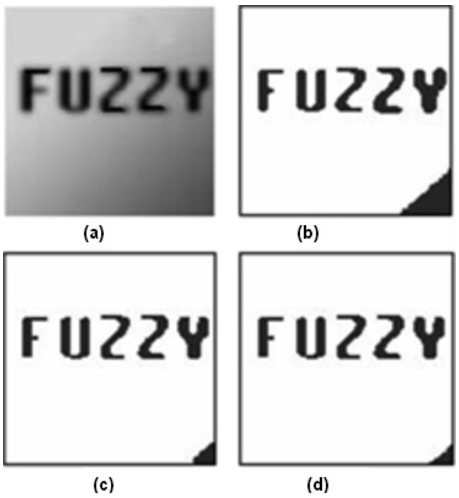

Figure 9. Segmentation of blurred scene. FDGA-Seg Iterations=50. (a) the blurred scene, (b) ICM result, (c) FDGA-Seg master-slave result, (d) FDGA-Seg Island result.

Whereas, ICM fails to enhance the quality of the segmentation, because the real image violates the assumed noise model.

The second implementation is the island-MAS. In Figure 11(a), the observed image represents blood with a cast shadow of cells having circle shapes. The two FDGA-Seg results are similar and better than the ICM one, which is not able to eliminate well the background noise.

Figure 12(a) shows a noisy scene which presents a half of a fruit. The three color segmentation of the ICM result cannot extract well the fruit parts out of its background. However, the results of FDGA-Seg show the features of the fruit in two FDGA-Seg results. Also, we show that our FDGA-Seg decomposes the segmentation in great objects, while the ICM tries unsuccessfully to detail the segmentation.

This FDGA-Seg robustness is due to a great variety of input data obtained by defuzzification

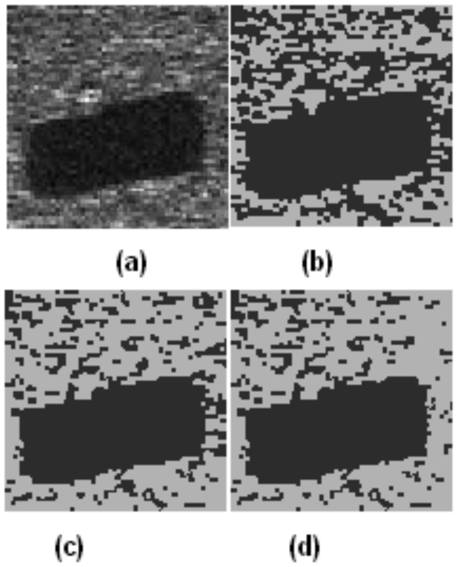

Figure 10. Segmentation of a sonar image. FDGA-Seg iterations=100 and $\alpha = 0$. (a) a cylindrical object shadow, (b) ICM result on (a), (c) FDGA-Seg master-slave result on (a), (d) FDGA-Seg island result on (a).

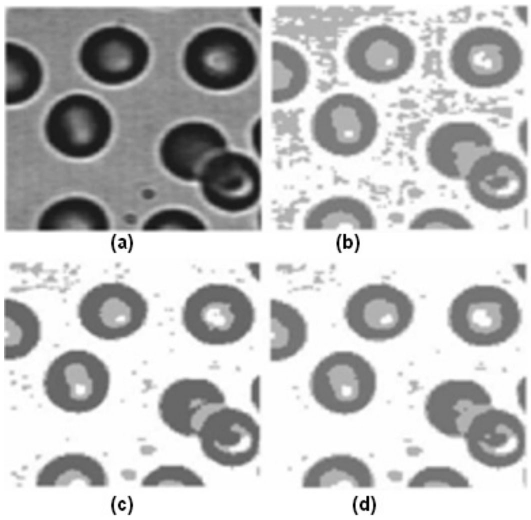

Figure 11. Segmentation of a blood image. FDGASeg iterations= 50. (a) the image, (b) ICM result, (c) FDGA-Seg master-slave result, (d) FDGA-Seg Island-MAS result.

of the fuzzy initial image. These different starting points permit the different agents to access any configuration in the solution space.

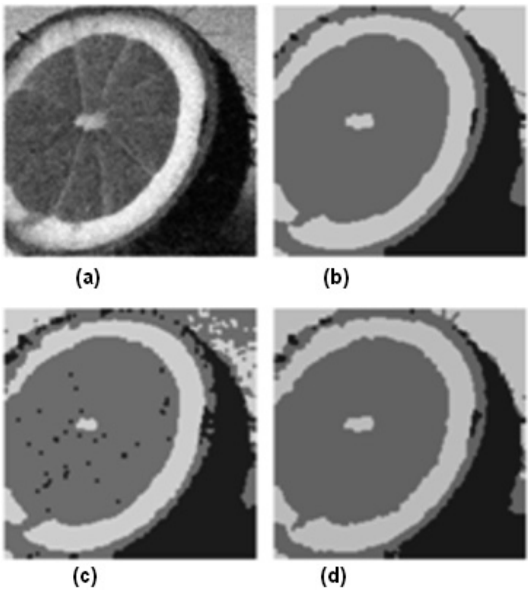

Figure 12. A three-class segmentation of a natural scene. FDGA-Seg iterations=50.
(a) the scene, (b) FDGA-Seg master-slave result,
(c) ICM result, (d) FDGA-Seg Island-MAS result.

5. Conclusion

We have introduced a new fuzzy distributed evolutionary approach for image segmentation. The competition/cooperation activity is interpreted by an iterative fuzzification/defuzzification process. In fact, the FDGA-Seg increases the possibilities to find good segmentations across a number of parallel ICM processes, each one starts from its own possible sub-optimal image.

We have defined a new fuzzy representation of the image used as input discrete data for the proposed distributed approaches. The retrieval process of the judged good information can be made by parallel deterministic processes instead of the genetic algorithms because it is completely clear that the role of the genetic algorithm is to offer good starting points to an efficient deterministic processes. We can find in this fuzzy distributed genetic algorithm the answer to many questions posed in the classical distributed GA such as the premature convergence and diversity.

This FDGA-Seg can be extended to large applications and reinforces with advantage the importance of the distribution. In order to assess the validity and the performance of the FDGA-Seg, we have applied our MASs on synthetic and real scenes. The experimental results are very encouraging and show clearly the robustness and the fast convergence of such approach.

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